PLANT-LEVEL PRODUCTIVITY AND THE MARKET VALUE OF A FIRM

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Abstract:
Some plants are more productive than others – at least in terms of how productivity is conventionally measured. Do these differences represent an intangible asset? Does the stock market place a higher value on firms with highly productive plants? This paper tests this hypothesis with a new data set. We merge plant-level fundamental variables with firm-level financial variables. We find that firms with highly productive plants have higher market valuations as measured by Tobin's q – productivity does indeed have a price.

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I. Introduction

Does productivity have a price? It is well know that we observe large, persistent differences in the productivity of plants within narrowly defined industries (cf., Bartelsman and Dhrymes, 1991; Baily, Hulten and Campbell, 1992; Olley and Pakes, 1997; and Dwyer, 1998). If high relative productivity represents a true competitive advantage, then it should act as an intangible asset and firms with highly productive manufacturing plants should have high market valuations. The data set analyzed in this paper merges firm-level Compustat variables with plant-level Census data. Consequently, Tobin's *q* – the market value of a firm divided by the replacement value of its capital stock – can be matched with measures of plant-level productivity. This data set enables us to test the hypothesis that highly productive manufacturing plants act as an intangible asset for the firms that own them. We follow a methodology first implemented by Griliches (1981).[1]

Highly productive manufacturing plants could act as an intangible asset for a variety of reasons. Rather than representing a true efficiency advantage, what we measure as high productivity could actually be the result of some firms being able to charge high markups due to barriers to entry or superior marketing.[2] Alternatively, they could be the product of favorable supply or demand shocks that the market has not yet adjusted to. While we cannot eliminate these alternative hypotheses, we do our best to control for them by looking at productivity differences relative to a narrowly defined

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[1] For a review of this literature see Hall (2000).

industry and controlling for other types of intangible assets that may enable a firm to charge high markups, such as advertising and research and development (R&D). We find that firms with highly productive manufacturing plants tend to have high *q*s – even when using narrow industry definitions and controlling for other types of intangible assets. Thus we find that plant-level productivity acts like an intangible asset.

This paper is organized as follows. The next section discusses the theoretical considerations relevant to this analysis. The third and fourth sections discuss building the data set, constructing the variables and some econometric issues. A preliminary analysis that narrows the set of productivity measures that we consider is found in the fifth section, which is followed by a presentation of findings. The final section contains our concluding remarks.

II. Theoretical Considerations

Following Cockburn and Griliches (1988) we start with a definitional model. Under a rational stock market, a firm's value can be written as

$$V = b[K + d\ \Omega],$$

where V is the market value of the firm, b is the average multiplier of market value relative to replacement value, K is the value of the firm’s tangible capital, Ω is a vector of

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[2] Productivity measures almost always us revenue-based measures of output. Consequently, a firm that is able to charge a high markup will tend to look like a highly productive firm.

variables representing the firm's intangible assets and δ is its relative shadow price vector. With some algebraic manipulation one can obtain

$$q = a + d\left(\frac{\Omega}{K}\right),$$

where $q \equiv \log\left(\frac{V}{K}\right)$, i.e., the log of Tobin's q. In essence, Griliches (1981) and Cockburn and Griliches (1988) regress Tobin's q onto a vector of intangible assets. They focus on R&D investments and the stock of patents. Our innovation is to include the productivity of the firm's manufacturing plants as an intangible asset into the vector of intangible variables.

What is productivity and why would it be an intangible asset?

While there are many concepts of productivity and many ways to measure it, most people would agree that one firm is more productive than another if it can produce more output with the same inputs as another firm. Operationalizing this seemingly innocuous statement is inherently problematic since no two firms produce the same output or use the same inputs. In this paper, we measure productivity as the ratio of value added[3] to an index of inputs at the plant level, which we then aggregate up to the firm level. It is essential to recognize that these measures are revenue based. Both a firm that can sell a differentiated product at a high markup and a firm that is a low-cost producer will be observed to have high productivity measures. If being a low-cost producer or charging a

[3] Value added is the difference between a firm's revenue (total value of shipments) and the value of its material inputs. (A material input is an input into the production process that has a useful lifetime of less than a year.)

high markup makes a firm highly profitable, then our productivity measure should behave like an intangible asset and increase the value of the firm.

Why would one firm be more productive than another?

One can think about two types of differences in productivity: *between*-industry differences and *within*-industry differences. Firms in one industry may be able to produce more revenue than firms in a second industry with the same inputs if there are barriers to entry in the second industry and thus corresponding differences in profitability. Alternatively, there could be industry-specific supply or demand shocks that the market has not fully adjusted to that could lead to differences in efficiency and profits across industries. These industry differences in profitability would lead to varied market valuations.

Depending on the theoretical model, within-industry differences in productivity may or may not display a positive relationship to a firm's value. For example, any model in which *ex ante* uncertainty regarding the outcome of investments exists (whether the investments are in physical capital, R&D, advertising, or human capital) will predict a positive relationship between productivity and Tobin's q: *ex post*, firms that make successful investments will have high productivity and a high market value relative to the replacement cost of their capital (cf., Jovanovic, 1982; Dixit, 1992; and Hopenhayn, 1992). In contrast, models in which productivity differentials are embodied in capital (cf., Cooley, Greenwood and Yorukoglu, 1997) or are the product of a deterministic learning-by-doing process (cf., Parente, 1994) do not predict a positive, monotonic relationship between productivity and Tobin's q.[4]

In light of these differing implications, we test whether or not a firm's productivity is positively related to a firm's Tobin's q. Further, we explore whether between-industry or within-industry differences in productivity have a larger effect on a firm's q.

Other types of intangible assets

Many other factors besides productivity may also affect the value of a firm. Consequently, we include a vector of control variables to account for these factors. Firms make investments in advertising and R&D, because they expect these investments to increase future cash flows – at least in the long run. Therefore, one would expect firms with substantial expenditures on advertising and R&D to have a higher return on physical capital and higher Tobin's q on average. We include R&D and advertising expenditures as percentages of the firm's total assets into the vector of intangibles.

Companies also buy other types of assets, such as patents and trademarks, to grow their cash flows. Firms classify these assets as intangibles on their balance sheets. The largest component of intangibles will typically be "goodwill," which represents assets

[4] In Cooley, Greenwood and Yorukoglu's model, for example, productivity differences are embodied in capital. Therefore, they do not yield a competitive advantage, because the new capital is available to everyone. All productivity differentials between plants are the product of not measuring capital in efficiency units. Once capital is measured in efficiency units, any observed variance in productivity is the result of measurement error and devoid of economic content. In Parente's model of staggered upgrading of technologies followed by a deterministic learning of the new technology, when a plant upgrades its technology its productivity falls, but its value remains unchanged.

derived from the acquisition of other companies.[5] These acquired assets are included in the denominator of Tobin's q and should be reflected in the numerator of Tobin's q or else the acquirer would not have bought the acquiree. Nevertheless, it is possible to have excess returns on investments in acquisitions to the extent that companies realizes synergies and/or market power when they acquire other companies. If the return on investment for M&A activity is above the required rate of return, then the market value of the company should reflect these returns, and firms with large stocks of intangible assets would have high Tobin's q. We test this hypothesis by including intangible assets as a percent of a firm's total assets in our vector of control variables.

A firm's lack of access to capital markets can detract from its value in several ways. First, a firm facing liquidity constraints cannot expand as fast as it would otherwise choose. Second, a liquidity-constrained firm may need to choose inventory policies that differ from its optimal inventory policy if it were not liquidity constrained. Following the investment literature (cf., Fazzari, Hubbard and Petersen, 1998; and Gilchrist and Himmelberg, 1995), we incorporate whether or not a firm pays a dividend into our vector of control variables.[6]

Firms may have dissimilar costs of capital, because they have different levels of risk. According to CAPM, the required return on a firm's assets is increasing in its market b. Therefore, to the extent that productivity controls for the rate of return that a

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[5] When a company buys another company, the book value of the acquired company's assets is incorporated into the book value of the acquiring firm's assets. The difference between what the company paid for the acquired company and the acquired company's book value is recorded as "goodwill" on the balance sheet.

[6] Experimentation using the presence of a bond rating instead of dividend payments produces similar results.

firm earns on its asset base, a company with a high market b is expected to have a lower q. Consequently, we include an estimate of market b in the vector of control variables.

In essence, we run a regression of Tobin's q onto productivity, which is measured at the firm level. We use a log-linear specification so that the coefficients can be interpreted as elasticities. We also include a vector of control variables (besides productivity) that could have a bearing on the value of the firm as described above. Finally, we econometrically examine the question of whether differences in productivity between industries or differences within industries have a bigger impact on Tobin's q.

III. Building the data set and variable construction

We combined two separate data sets: Standard and Poor's Compustat, which contains firm-level financial variables, and the Census Bureau's Longitudinal Research Database (LRD), which has plant-level fundamental variables (e.g., the outputs and inputs of the plant). The resulting data set consists of over 993 firms that report R&D expenditures in 1996 (Table A.1). The firms in the sample represent $2.7 trillion in sales and 11 million in employees in 1996 (Table A.2). By tracking this cross-section forward and backward, we have constructed a panel of firms where the Compustat variables run from 1989 to 1998, and the LRD variables run from 1976 to 1997. Appendix I provides a description of how the merge was done and provides two tables of summary statistics.

Variable construction

Productivity measures

Although we have plant-level measures of inputs and outputs, we want to construct a firm-level measure of productivity. The firms in our sample typically have many plants that operate in various four-digit industries. This presents an issue, because measures of total factor productivity are rooted in a Cobb-Douglas production function. Such a production function at the plant level will only aggregate up to a firm-level Cobb-Douglas under a very restrictive set of assumptions.

Our approach is to construct four measures of productivity and perform a preliminary sensitivity analysis to see which ones are the most informative.

Labor productivity (lp)

To measure the labor productivity of the firm's manufacturing plants, we first sum up at the firm level both value added (our measure of output) and total employment. Then we simply take the ratio and then take its log.

Capital productivity (kp)

We measure capital productivity in a fashion analogous to labor productivity. Value added and gross capital stock of each firm is summed. We take the ratio of the two and then take its log.

Average productivity (ap)

$$ap = \frac{kp + lp}{2}$$

This is simply the average of the log of labor productivity and the log of capital productivity. This definition can be reached by taking a firm-level Cobb Douglas production function, solving for productivity and setting the exponent terms both to ½:

$$Y = AL^{a}K^{1-a} \Rightarrow A = \left(\frac{Y}{L}\right)^{a}\left(\frac{Y}{K}\right)^{1-a},$$

where Y is output, L is labor inputs and K is capital inputs. Taking logs and setting $\alpha = \beta = 0.5$ yields the above definition of average productivity, *ap*.

Average plant-level tfp – (tfp)

Following Dwyer (1998) we measure the productivity at the plant level relative to the four-digit industry mean in that year. Specifically,

$$X_{klt} = \frac{Y_{klt}}{L_{klt}^{a_l} K_{klt}^{1-a_l}},$$

where *k*, *l* and *t* index the plant, the four-digit industry and the year, respectively, and a_l is the coefficient from an estimate of a constant returns-to-scale Cobb-Douglas production function for the plant's four-digit industry. X_{klt} is thus a value of total factor productivity for each plant; we use x to denotes its logarithm. From this measure we can compute relative productivity by calculating logs and subtracting out the time-industry mean in each year:

$$\tilde{x}_{klt} = x_{klt} - x_{\bullet lt},$$

where $\tilde{x}_{klt}$ has the following interpretation.[7] If $\tilde{x}_{klt}$ =0.35, then plant k produced 35% more output with the same inputs than the average plant in its four-digit industry during that year. To convert this plant-level measure of productivity to the firm level, we simply take a weighted average of all the firm's plants, using the number of employees working at the plants as the weights. We denote this measure of productivity as tfp.

The construction of this productivity measure eliminates any between industry effects of productivity on Tobin's q. Therefore, the ability of this variable to predict Tobin's q will address the possibility of productivity differences within industries impacting the value of a firm.

Tobin's q

One traditionally defines Tobin's q as the ratio of the firm's market value to the replacement value of its assets. To construct this measure, we follow Himmelberg, Hubbard, Palia (1999) and use the market value of the outstanding common stock plus the estimated value of the preferred stock plus the book value of total liabilities as the market value of the firm, and the book value of total assets for the replacement value of the firm. We denote this variable as Q and its logarithm as q.

[7] I am adopting the notation that $tfp_{\bullet lt} = \frac{\sum_k tfp_{klt}}{N}$,i.e., the time-industry average of productivity.

The vector of control variables

Table 1: The vector of control variables

Variable	Explanation
log(Adv:Cap)	Log of advertising expenditures to total assets
Adv is zero or missing	1 if Adv is zero or missing
log(RnD:Cap)	Log of R&D expense to total assets
RnD is zero or missing	1 if RnD is zero or missing
log(Intang:Cap)	Log of intangible assets to total assets
Intang is zero or missing	1 if Intang is zero or missing
Market β	Market β as computed by Compustat
Does not pay a dividend	1 if the firm does not pay a dividend
log(Emp)	Log of total employees

For advertising-to-capital, R&D-to-capital and intangibles-to-capital variables we use logs of the ratios so that the coefficients can be interpreted as elasticities.[8] In the event that advertising, R&D or intangibles are missing or reported as zero, we set the value to zero and construct an indicator variable for whether the value is zero or missing, which is included as a control variable. The estimate of a firm's market β was obtained from Compustat. An indicator variable equals one if a firm pays a dividend. Finally, we include the log of the total number of employees as a control variable for any potential scale effects.

[8] For a discussion of the relative merits of a linear versus log-linear specification see Hall (2000).

IV. Econometric issues

The general equation that we wish to estimate is

$$\tilde{q}_{ijt} = g_1 \tilde{a}_{ijt} + \tilde{X}_{ijt} y + e \ ,$$

where i, j and t denote the firm, two-digit industry and year, respectively; q denotes the log of Tobin's q; a denotes the log of the firm's productivity; X denotes the vector of control variables; and $\tilde{z}_{ijt}$ denotes either $z_{ijt} - z_{\bullet jt}$, if year and two-digit industry effects are controlled for, or $z_{ijt} - z_{\bullet\bullet t}$, if only year effects are controlled for.

Two important issues regarding the measurement of productivity influence the estimation procedure. First, current productivity, as reported in Census data, contains a persistent component, but also contains unusual accounting events, transitory demand shocks and transitory measurement error (cf., Baily, Hulten and Campbell, 1992). The productivity that will impact the value of the firm is the persistent component of productivity. Using lags of productivity as instruments for current productivity can solve this problem.[9]

Second, we would like to measure the productivity of the firm as a whole, but what we actually observe is the productivity of the firm's US manufacturing plants. For a company whose US manufacturing operations are small relative to their operations as a whole, we would expect a weak relationship between the productivity of US

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[9] In order for lags of productivity to be valid instruments for current productivity, it is necessary that the measurement error in current productivity is independent of the measurement error in the lags of productivity. We use four lags of productivity as instruments. Out of concern about serially correlated measurement error, we have experimented with excluding the first and second lags of productivity as instruments and found minimal impact on the results.

manufacturing plants and the firm's market value. Conversely, if the majority of a firm's employees work in the US manufacturing plants then we would anticipate a stronger relationship. We deal with this issue by running the regression on two samples. In the first sample, we include all firms for which the ratio of US manufacturing employment of the firm to the firm's total worldwide employment lies between 0 and 1. In the second sample, we include all firms for which the ratio of US manufacturing employment of the firm to the firm's total worldwide employment lies between 0.5 and 1. We predict a bigger coefficient on productivity for the latter, restricted sample.

V. Preliminary sensitivity analysis

In this section, we examine the relationships between the different productivity measures and Tobin's *q*. The intent is to narrow the scope of the analysis – to choose two measures of productivity to focus on for the remainder of the paper.

Tables 2 and 3 present correlation matrices of Tobin's *q* and the four candidate measures of productivity.[10] In Table 2, all variables have been transformed so that the mean of each variable in each year is zero, which eliminates time effects. In Table 3, all variables have been transformed so that for every year, the mean of each variable in every two-digit industry (as reported in Compustat) is zero, which eliminates time-industry effects.

Overall the correlation of the productivity measures with Tobin's *q* are lower when we eliminate time-industry effects, which suggests that between-industry differences in productivity may be more important than within-industry differences in determining Tobin's *q*. Of the productivity measures, *ap* is the most highly correlated with Tobin's *q*. The measure of productivity that eliminates four-digit industry effects, *tfp*, is the least highly correlated, which is perhaps not surprising. We choose to focus on *ap* and *tfp* for the remainder of the paper, because this pair is the most and least highly correlated, respectively, with of Tobin's *q*. By looking at *tfp*, we "stack the deck against" finding that productivity has a price because it is measured relative to narrowly defined industries.

[10] Following Baily, Hulten and Campbell (1992), we eliminate outliers according to the following rule: we restrict the sample to observations in which productivity is within plus or minus 200% of the industry average in that year.

Correlation matrices

Table 2: The correlation matrix of different measures of productivity and Tobin's *q* (controls for year effects)

	q	*lp*	*kp*	*ap*	*tfp*
q	1.00	0.30	0.19	0.31	0.15
lp		1.00	0.14	0.71	0.64
kp			1.00	0.77	0.034
ap				1.00	0.41
tfp					1.00

All measures are in logs and are standardized by year. All coefficients are statistically significant ($p<0.01$). The sample sizes range from 4,673 to 5,046.

Table 3: The correlation matrix of different measures of productivity and Tobin's *q* (controls for year-industry effects)

	q	*lp*	*kp*	*ap*	*tfp*
q	1.00	0.25	0.18	0.26	0.16
lp		1.00	0.22	0.72	0.71
kp			1.00	0.81	0.02
ap				1.00	0.41
tfp					1.00

All measures are in logs and are standardized by their two-digit industry and year. All coefficients are statistically significant ($p<0.01$), with the exception of (*kp*, *tfp*). The sample sizes range from 4,673 to 5,046.

VI. Findings

Table 4 presents regressions of Tobin's *q* onto *ap* and *tfp*. Columns 1, 3, 5 and 7 are run on the full sample, while columns 2, 4, 6 and 8 are run on a sample restricted to cases in which 50 percent or more of the firm's employees are represented in its US manufacturing plants. In general, the coefficients are bigger under the restricted sample, as expected. The difference, however, is less dramatic for *tfp* than for *ap*. Columns 3, 4, 7 and 8 instrument for current-year productivity using lags of productivity, whereas columns 1, 2, 5 and 6 do not. For *ap*, instrumenting for productivity yields bigger coefficients on productivity. Once again, the effect is bigger for *ap* than for *tfp*.

Columns 1, 2, 3 and 4 account for time effects, whereas Columns 5,6,7 and 8 account for time-industry effects. In the case of *ap*, controlling for time-industry effects yields smaller coefficients, suggesting that between-industry variation in productivity is a more important driver of market value than within-industry variation. In the case of *tfp*, controlling for time-industry effects does not change the coefficients appreciably, as predicted, since the variable *tfp* was constructed to eliminate industry differences in productivity at the outset.

Tables 5 and 6 present regressions of Tobin's *q* onto *ap* and a vector of control variables. Table 5 and 6 control for time and time-industry effects, respectively. Table 7 presents regressions of Tobin's *q* onto tfp and a vector of control variables, controlling for time-industry effects. Adding other control variables into the regression tends to lower the magnitude of the coefficient on productivity (*ap* or *tfp*) somewhat. Nevertheless, the coefficient is still positive and significant in every regression, which is strong evidence that the productivity of a firm's manufacturing plants positively impacts a firm's market value.

Controlling for time-industry effects lowers the magnitude of the coefficient on *ap* (comparing Table 5 to Table 6). This suggests that between-industry differences in productivity may have a bigger impact on market valuations than within-industry differences in productivity.

Even after controlling for productivity, expenditures on R&D and advertising have a positive impact on Tobin's *q*, as anticipated. The indicator variables for whether or not the variable is missing or zero has a large, negative coefficient, as expected due to the log-linear specification.[11] The coefficient on intangibles is always insignificant. Therefore, intangibles do not appear to have an "excessive" impact on a firm's market value.

Not having access to financial markets appears to hurt a firm's value. Firms that do not pay a dividend have a market value that is 7% lower, *ceteris paribus*. However, this finding does not hold across all specifications.

There is evidence of scale effects. The Tobin's *q* of firms that employee 10% more people than average is 0.1% - 0.3% bigger, *ceteris paribus*, and statistically significant across all full sample specifications. Counter to intuition, firms that are riskier – as measured by their market β – are worth more. This finding is robust across all specifications.

[11] Including an indicator variable for whether not a variable is missing or zero in a log-linear specification yields a coefficient with a somewhat idiosyncratic interpretation. For example, the -0.30 coefficient on *Adv is zero or missing* (in regression 1 on Table 5) has the interpretation that a firm that does not advertise has a Tobin's q that is 30% lower than that of a firm whose ratio of Adv:K is 100% (whose log(Adv:K) is zero).

Regression results

Table 4: Regression of Tobin's *q* onto productivity

Table 4a:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ap	0.25**	0.35**	0.30**	0.36**	0.22**	0.29**	0.26**	0.30**
	(0.012)	(0.02)	(0.016)	(0.027)	(0.012)	(0.021)	(0.016)	(0.028)
N	3,644	1,850	3,203	1,610	3,644	1,850	3,203	1,610
Restricted sample?[a]	no	yes	no	yes	no	yes	no	yes
Instruments?[b]	no	no	yes	yes	no	no	yes	yes
Year-industry effects?[c]	no	no	no	no	yes	yes	yes	yes

Table 4b:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tfp	0.16**	0.18**	0.18**	0.18**	0.15**	0.19**	0.19**	0.21**
	(0.014)	(0.024)	(0.03)	(0.044)	(0.013)	(0.023)	(0.029)	(0.043)
N	5,098	2,471	2,007	1,140	5,098	2,471	2,007	1,140
Restricted sample?[a]	no	yes	no	yes	no	yes	no	yes
Instruments?[b]	no	no	yes	yes	no	no	yes	yes
Year-industry effects?[c]	no	no	no	no	yes	yes	yes	yes

The dependent variable is the log of Tobin's *q*. Standard errors are reported in parentheses. * and ** indicate significance at the 95 and 99 percent level, respectively. All regressions control for year effects.

[a]The sample is restricted when only firms with an employment ratio (the ratio of the firm's LRD employees to the firm's Compustat employees) of between 0.5 and 1 are included. The unrestricted sample includes all firms with an employment ratio of less than 1.

[b]Indicates whether or not productivity has been instrumented for with four lags of productivity.

[c]Indicates whether or not year-industry effects have been controlled for.

Table 5: *ap* with year effects

Variable	2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
ap	0.26**	0.30**	0.25**	0.31**
	(0.016)	(0.028)	(0.016)	(0.029)
log(Adv:K)	0.072**	0.058**	0.062**	0.045**
	(0.011)	(0.017)	(0.011)	(0.017)
Adv is zero or missing	-0.3**	-0.27**	-0.26**	-0.22**
	(0.045)	(0.068)	(0.044)	(0.068)
log(RnD:K)	0 .043**	0.054**	0.044**	0.049**
	(0.0077)	(0.011)	(0.0077)	(0.011)
RnD is zero or missing	-0.2**	-0.23**	-0.21**	-0.21**
	(0.032)	(0.046)	(0.032)	(0.047)
log(Int:K)	0.00092	0.0026	0.00013	-0.0076
	(0.007)	(0.011)	(0.0068)	(0.01)
Int is zero or missing	0.037	0.073	0.053*	0.12**
	(0.026)	(0.04)	(0.026)	(0.04)
Market b	–	–	0.076**	0.07**
			(0.0074)	(0.0088)
Does not pay a dividend	–	–	-0.098**	-0.084**
			(0.016)	(0.023)
Log of emp	–	–	0.019**	0.012
			(0.0051)	(0.0081)
Sample Size:	3,203	1,610	3,200	1,609

Dependent variable is the log of Tobin's q. We instrument for *ap* using four lags, and we control for year effects.

Table 6: *ap* with year and industry effects

Variable	2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
ap	0.22**	0.27**	0.21**	0.28**
	(0.017)	(0.029)	(0.016)	(0.03)
log(Adv:K)	0.055**	0.045**	0.049**	0.031
	(0.011)	(0.017)	(0.011)	(0.017)
Adv is zero or missing	-0.23**	-0.21**	-0.21**	-0.16*
	(0.045)	(0.071)	(0.045)	(0.07)
log(RnD:K)	0.054**	0.056**	0.045**	0.043**
	(0.0083)	(0.012)	(0.0082)	(0.012)
RnD is zero or missing	-0.27**	-0.27**	-0.22**	-0.19**
	(0.037)	(0.053)	(0.037)	(0.053)
log(Int:K)	-0.0028	-0.011	-0.0036	-0.017
	(0.0068)	(0.011)	(0.0067)	(0.01)
Int is zero or missing	0.064*	0.14**	0.073**	0.17**
	(0.026)	(0.042)	(0.026)	(0.041)
Market b	–	–	0.078**	0.073**
			(0.0073)	(0.0088)
Does not pay a dividend	–	–	-0.076**	-0.074**
			(0.016)	(0.023)
Log of emp	–	–	0.015**	0.014
			(0.0052)	(0.0087)
Sample Size:	3,203	1,610	3,200	1,609

Dependent variable is the log of Tobin's q. We instrument for *ap* using four lags, and we control for industry-year effects.

Table 7: *tfp* with year and industry effects

Variable	2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
tfp	0.17**	0.18**	0.11**	0.13**
	(0.029)	(0.043)	(0.03)	(0.046)
log of Adv:K	0.058**	0.047	0.048**	0.03
	(0.017)	(0.024)	(0.017)	(0.024)
Adv is zero or missing	-0.23**	-0.21*	-0.19**	-0.17
	(0.069)	(0.096)	(0.067)	(0.095)
log of RnD:K	0.061**	0.058**	0.052**	0.045**
	(0.011)	(0.015)	(0.011)	(0.015)
RnD is zero or missing	-0.32**	-0.34**	-0.29**	-0.28**
	(0.048)	(0.068)	(0.047)	(0.067)
log of Int:K	0.0024	-0.014	0.006	-0.016
	(0.0095)	(0.015)	(0.0093)	(0.015)
Int is zero or missing	0.078*	0.16**	0.071*	0.18**
	(0.036)	(0.057)	(0.035)	(0.055)
Market b	–	–	0.078**	0.089**
			(0.0091)	(0.011)
Does not pay a dividend	–	–	-0.028	-0.077**
			(0.02)	(0.029)
Log(# of employees)	–	–	0.03**	0.022
			(0.0074)	(0.012)
Sample Size:	2,007	1,140	2,006	1,139

Dependent variable is the log of Tobin's q. We instrument for *ap* using four lags, and we control for year effects.

VII. Conclusion

The basic message of this paper is that productivity does indeed have a price: firms with highly productive manufacturing plants have higher market valuations as measured by Tobin's *q*. While this could be the product of some firms having a market niche that allows them to charge a high market-up which is measured as high productivity, we attempt to control for this hypothesis by looking at productivity differentials within narrowly defined industries and by controlling for other types of assets that would allow a firm to charge a high mark-up. We still find that productivity acts as an intangible asset.

Between-industry differences in productivity appear to be more important than within-industry differences, because the coefficients on productivity are consistently smaller if one controls for time-industry effects. This reduction in the magnitude of the coefficients is what one would expect if there were idiosyncratic measurement error in firm-level productivity.[12]

We also find that other intangible assets have an impact on market value after controlling for productivity. These assets include R&D and advertising expenditures. Interestingly, investments in other companies, as captured by intangible assets on the balance sheet, do not appear to have an excess return as they do not predict Tobin's *q*.

Access to financial markets appears to matter. Firms that do not pay dividends o r do not have a bond rating (traditional proxies for liquidity constraints) have lower market

[12] Put simply, if there is idiosyncratic measurement error in firm-level productivity, then these errors will tend to average out when we look between industries. Therefore, the

valuations after controlling for Tobin's q. This finding is consistent with the hypotheses that (1) these proxies do measure liquidity constraints and (2) liquidity constraints do have a negative impact on the value of the firm.

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downward bias associated with measurement error will be lower in the between estimates than in the within estimates (cf. Griliches, 1986).

Appendix I: Merge Methodology and Sample

The database used in this paper was derived from a merge of the Census's 1992 Survey of Industrial R&D (a survey of R&D performing firms) with Standard and Poor's Compustat variables, performed by Bill Long. Long's data could then be merged into the LRD because the Survey of Industrial R&D uses the same the firm identification numbers (*firmnums*) as Long's merged file.

Long provided us with a file that contained 3,221 observations on the following variables: CUSIP (the field used to identify firm's in Compustat), firmnum (the number used by the Census to identify a firm), company name, and some information on sales and R&D expenditures. The Long merge was based on 1993 Compustat data; the Compustat variables used in the paper were extracted in early 2000. In order to better match to Long's 1993 extract, we incorporate companies from Compustat's Research File, which includes companies that have since been acquired or gone out of business. Matching our extract to Long's yielded a data set with 2,263 useable "crosswalk" observations containing both *CUSIP* and *firmnum*.

The next step in the matching process was to collect all Compustat data for the firms in the "crosswalk" file over the time horizon of the current Compustat extraction, i.e., 1989-1998. This yielded a data set with 22,620 firm-year observations (2,262 firms) over these years. We then matched these firms, by *firmnum* and year, to a firm-level data set that we produced from the LRD from 1976-1997. This merge generated a data set with 26,169 firm-year observations, of which those prior to 1989 do not include Compustat data. Of the 2,262 firms this data set represents, 1,922 of them had valid LRD data for one or more years. Tables A.1 and A.2 provide summary statistics on the final sample.

Reasons why our Compustat-to-LRD match rate was not 100% may include (1) inconsistencies between the *firmnum* reported in the Survey of Industrial R&D and the LRD; (2) many firms performing R&D may not have US manufacturing plants that would appear in the LRD.

Table A.1: Number of matched firms in sample

Year	Number of Firms
1989	1,174
1990	1,170
1991	1,152
1992	1,399
1993	1,124
1994	1,077
1995	1,029
1996	993

Table A.2: Summary Statistics, 1996.

Two-digit SIC	Firms	Employees	Manufacturing employees	Total Sales	Total Value of Shipments	Total R&D Exp.	Total Advert. Exp.
Food and kindred products	77	2,310	731	$443	$273	$7.93	$21.58
Tobacco products	2	-	-	-	-	-	-
Textile mill products	45	893	440	$296	$146	$4.59	$1.32
Apparel and textile	28	1,504	580	$388	$254	$17.12	$6.05
Lumber and wood	48	633	373	$119	$100	$0.52	$0.15
Furniture and fixtures	25	155	79	$22	$13	$0.18	$0.32
Paper	33	501	170	$201	$70	$3.94	$4.41
Printing and publishing	37	911	220	$213	$63	$3.58	$1.67
Chemicals	113	930	289	$322	$135	$10.39	$4.40
Petroleum and coal	9	-	-	-	-	-	-
Rubber and misc. plastics	74	755	348	$129	$74	$3.83	$1.05
Leather products	8	-	-	-	-	-	-
Stone, clay, and glass	24	327	144	$96	$46	$1.89	$1.77
Primary metal ind.	50	389	264	$73	$70	$1.72	$0.01
Fabricated metal products	63	138	100	$22	$18	$0.35	$0.02
Industrial machinery and equipment	141	1,222	359	$296	$124	$17.15	$3.38
Electronic & other electric equipment	116	514	274	$111	$81	$8.09	$1.06
Transportation equipment	18	143	81	$24	$17	$0.37	$0.03
Instruments and related products	70	98	40	$15	$9	$1.24	$0.18
Miscellaneous	12	16	9	$3	$2	$0.06	$0.17
Total	993	11,439	4,501	$2,773	$1,495	$82.95	$47.55

Note: All dollar figures are in millions of dollars. Employees are in thousands. A - indicates that the information has been suppressed for confidentiality reasons. The totals are based on the reported information.

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